A Fire Severity Mapping System (FSMS) for Real-time Fire Management Applications and Long Term Planning:

Developing a Map of the Landscape Potential for Severe Fire in the Western United States

Gregory K. Dillon[1]*, Zachary A. Holden[2], Penny Morgan[3] and Bob Keane[1]

[1]USDA Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory, Missoula, MT USA

[2]USDA Forest Service, Northern Region, Missoula, MT USA

[3]University of Idaho, Department of Forest Resources, Moscow, ID USA

* Corresponding author: gdillon@fs.fed.us

Objective

- Produce a seamless, wall-to-wall, 30-meter raster geospatial layer covering all lands in 11 western states that:
  - builds on MTBS data to make predictions
  - depicts the probability of severe fire for each 30-m cell
  - can be made available for managers and scientists to download

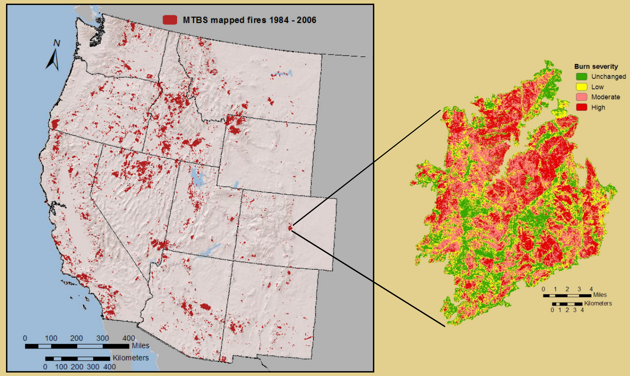
Background

- Fire severity mapping tools and technologies are critical for 1) identifying where and when fires may burn severely, 2) facilitating enlightened wildfire management, and 3) strategically implementing costly rehabilitation and restoration efforts (Lachowski *et al.* 1997; Eidenshink *et al.* 2007).
- Holden et al. (2009) demonstrated on the Gila National Forest that they could predict locations of high severity fire with over 80% accuracy, using satellite-derived fire severity data from the Monitoring Trends in Burn Severity project (MTBS) along with topographic and biophysical predictor variables.
- As part of the Fire Severity Mapping System project, we are using similar methods to develop a comprehensive, west-wide map of the landscape potential for severe fire.

Methods

Step 1a: Acquire and process burn severity data

- Acquire MTBS burn severity data (1984-2006) for the western U.S.
- Use Relative differenced Normalized Burn Ratio (RdNBR; Miller and Thode 2007)
- For each fire, use fuzzy C-means clustering (Holden and Evans, accepted) to create 4 classes



Step 1b: Compile candidate predictor variable data layers

Category	Data layer	Description
Climate[1]	MAT	Mean annual temperature
	MAP	Mean annual precipitation
	MonthT[2]	Average monthly mean temperature
	MonthM[2]	Average monthly min temperature
	MonthX[2]	Average monthly max temperature
	MonthP[2]	Average monthly total precipitation
	MTCM	Mean temperature in coldest month
	MMIN	Min temperature in coldest month
	MTWM	Mean temperature in warmest month
	MMAX	Min temperature in warmest month
	TDIFF	Summer-winter temperature differential
	DD5	Number degree-days >5º C
	DD0	Number degree-days <0º C
	FFP	Length of frost-free period
	AMI	Annual moisture index [DD5/MAP]
	PRATIO	Ratio of summer to total precipitation [GSP/MAP]
Topography	DEM	Elevation (USGS National Elevation Dataset)
• Slope / aspect transformations	CAT	Slope cosine aspect (Stage 1976)
	SAT	Slope sine aspect (Stage 1976)
	TRASP	Solar-radiation aspect index (Roberts and Cooper 1989)
	HLI	Heat Load Index (McCune and Keon 2002)
• Slope position and curvature	HSP	Hierarchical Slope Position (Murphy et al. in press)
	TPI	Topographic position index (Weiss 2001)
	LFI	Landform Index (McNab 1993)
• Topographic complexity	DISS	Martonne's modified dissection coefficient (Evans 1972)
	ERR	Elevation Relief Ratio (Pike and Wilson 1971)
• Contributing area	CTI	Compound Topographic Index (Moore et al. 1993)
• Solar radiation	SOL	Solar insolation (Kumar et al. 1997)
	PRR	Potential relative radiation (Pierce et al. 2005)

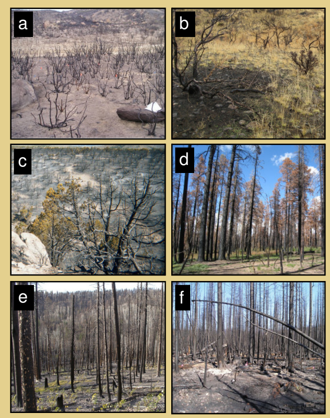
[1] Climate model = ANUSPLIN (Hutchinson 2000); Climate data source = A) climate normals 1961-1990 (Rehfeldt 2006), or B) climate normals 1971-2000 (NOAA-NCDC 2008, USDA FS-FHTET 2009)

[2] Variable is created for each month (e.g., janT, febT, etc.); multi-month groupings are also possible

Step 2: Develop statistical predictive models

Within distinct ecological regions across the West:

- Generate a large random sample of pixels (10,000 – 100,000+)
- Extract values for response (burn severity) and predictor variables at each sample location
- Use the Random Forests machine learning algorithm (Breiman 2001) to develop a predictive model of high severity potential



Examples of high severity fire different ecosystems around the West: (a) California chaparral, (b) big sagebrush steppe, (c) piny on-juniper woodland, (d) ponderosa pine forest, (e) southwest mixed-conifer/aspen forest, (f) northern Rockies mixed-conifer forest.

Step 3: Apply models spatially

- Produce a raster prediction surface for each region
- Merge rasters into a seamless layer for the West

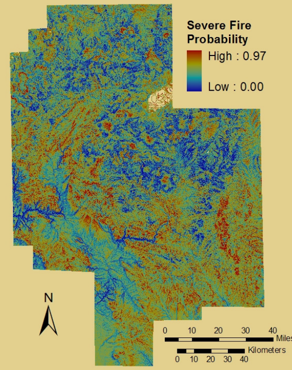


figure adapted from Holden et al. 2009

Step 4: Accuracy Assessment

- Determine error rates and misclassifications using independent field data:
  - Collect field data on selected fires from 2008, 2009, and 2010
  - Compare predicted areas of high severity with field observations
  - Produce contingency tables, calculate accuracy statistics

Deliverables

December 2010	Spatial database of climatic and topographic predictor variables
December 2010	Publication focusing on compilation of spatial database and methods for statistical modeling
December 2011	Final west-wide map of landscape potential for severe fire ("Landscape PSF Map")
June 2012	Summary journal publication

Expected Benefits

Values to Science

Increased understanding of:

- "bottom-up" landscape-level controls on fire severity
- relative contribution of climate and topography to burn severity
- conditions where fires are more likely to burn severely

Values to Management

- Provides an "on-the-shelf" resource for managers to use when evaluating the potential risks and effects associated with new fire events
- Integrates with other components of the Fire Severity Mapping System project (e.g., FOFEM simulation modeling) and existing severity products (e.g., BARC, MTBS) to create a suite of spatial fire severity data products
- RAVAR and WFDSS are immediate users of these products

Future Challenges

Topography and climate will be the primary predictors for the Landscape PSF Map. If we can reliably incorporate fuels data into the modeling, we may be able to produce a "Fuels PSF Map" and possibly an "Integrated PSF Map" that combines predictions based on climate, topography, and fuels.

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